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UNCERTAINTY AND THE STRATEGIC LAND USE/TRANSPORT PLANNING PROCESS

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Abstract:

Types of uncertainty encountered in the long term strategic planning process are identified: (a) uncertainity in information acquisition; (b) uncertainity in modelling; (c) uncertainty in the values of interest groups who influence decisions; (d) uncertainty in whether a sufficient set of alternative plans have been tested; and (e) uncertainty in the environment external to the planning process. Research into ways of reducing uncertainty in the second, third and fourth areas is reported. This includes a sensitivity analysis of an urban travel demand model and the application of interactive multi-objective programming to help decision-makers examine competing objectives.

INTRODUCTION

A transport planner, when admitting to uncertainty, is being professionally honest. Uncertainty precludes the construction of a definitive analytical model of the land use/transport system Even if such a model existed the uncertainty of the future - especially with changes in popular preferences - would detract from its application to any long-term planning process. Coping with uncertainty than is the essence of responsible advice offered to decision-makers.

The different components of uncertainty in the strategic land use/transport planning process are identified By recognising these uncertainties it becomes possible to devise ways of reducing uncertainty. Examples included in this paper are sensitivity analysis of the parameters of urban travel demand models, and interactive multi-objective programming.

UNCERTAINTY IN THE PLANNING PROCESS

Figure 1 is a diagrammatic representation of the strategic planning process. The components are the physical environment (the land use/transport system), the planning process, the political system (policy guidance) and an implementation agency. The interactions shown in this diagram eventually lead to the implementation of a preferred plan, which changes the physical environment. Traditionally a closed-system approach has been adopted by ignoring uncertainty and claiming pure rationality (O'Sullivan, et al, 1979, p.85). However, we suggest there are five types of uncertainty, as indicated in Fig. 1.

Type I: uncertainties in the reliability of the information about the existing physical environment because of unsatisfactory data collection methods or incomplete knowledge.

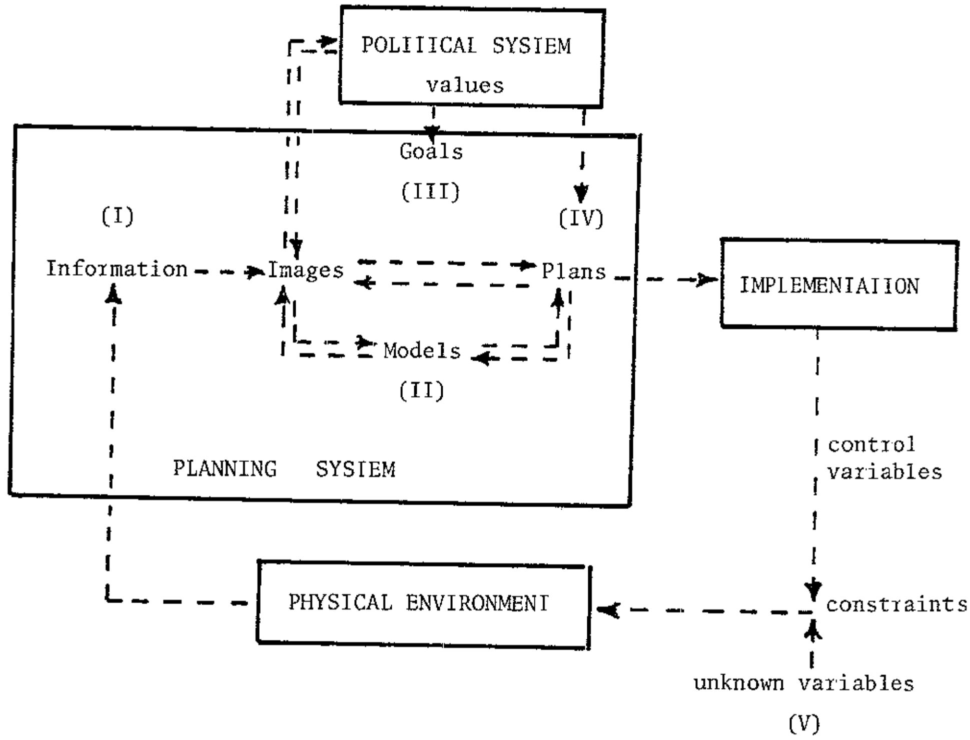
Type II: uncertainties in the correct specification of models which describe the interactions between land use, traffic and transport, and in the ability of these models to make accurate forecasts.

Type III: uncertainties in the values of policy-makers and in future community preferences which make it difficult to set clear planning goals and objectives.

Type IV: uncertainties in whether a comprehensive range of alternative plans have been generated and evaluated.

Type V: uncertainties in the actions of groups external to this planning process but who might effect some change to the physical environment.

Broadly, there are three ways of handling these components of uncertainty Friend and Jessop (1977), in a study of local government



( ) - Type of uncertainty

Figure 1: Uncertainty and Planning

(Source: after Faludi, 1973, Chapter 4)

planning in Coventry, suggest that the uncertainty in choosing between alternative plans can be reduced by conducting more research (Types I, II and IV), securing more policy guidance (Type III), and achieving more co-ordination with other government departments and interest groups (Type V). The effectiveness of these approaches is examined in the context of transport planning in South-East Asian cities by Black (1980a).

Here we concentrate on the role of research and are primarily concerned with reducing Type II, III and IV uncertainties. First, the results from a sensitivity analysis of the parameters of conventional models of urban travel demand are reported. The fact that decisions are not highly dependant on the model specification lends support to the view that 'simplified models' are sufficiently accurate for strategic planning purposes. An additional advantage would be that more resources could be devoted to the generation and testing of alternative plans. Second, the use of multiple objective programming is explored. This technique helps make explicit the objectives of policy-makers, allows the implications of competing objectives to be recognised, and provides a suitable framework for analysing changes in objectives with time.

SENSITIVITY ANALYSIS

Given uncertainty in the accuracy of model forecasts the question to ask is whether the results alter the conclusions made at the evaluation stage of the planning process. Sensitivity analysis is a study to determine the responsiveness of the conclusions of an analysis to the changes (or errors) in model parameters and/or variables used in the analysis. As an example, a study was designed to assess the effect of controlled changes in the parameters of trip distribution models on the resulting pattern of transport network link assignments.

A hypothetical study area was partitioned into seventeen zones. The zone centroids were connected by a symmetrical ring-radial transport network of forty-eight directional links. Only two land uses were considered - homes and workplaces. The spatial distribution of workers and jobs reflected an actual city with central employment core, and a predominantly residential outer fringe. The mean trip length for the journey from home to work was assumed to be 6 km.

Six gravity-type trip distribution models were tested. They differ by model constraint (unconstrained, production constrained, fully-constrained) and by the impedance function of distance (exponential and power). Each model was calibrated in the usual way and then the parameter was varied systemmatically. The outputs produced for each variation - the model origin-destination matrix - formed the input to an all-or-nothing traffic assignment model (an ICL 1900 Series Traffic Assignment Program package). The network link assignments were examined for each test-run.

The conclusion drawn was that link assignments were in general relatively stable for a wide range of calibration parameters. For each model, a range was found where the ranking of the links by the amount of traffic assigned was consistent. Table 1 summarises the results. The 'insensitive' range is expressed in terms of the mean trip length produced by each combination of model and parameter value because the exponential and power formulations involve very different numbers associated with the parameter.

Table 1: Gravity Model Sensitivity Analysis

Model Constraint	Impedance Function	Insensitive Range (km)	Latitude (km)
Unconstrained	Exponential	5.92 - 6.08	0.16
Unconstrained	Power	5.85 - 6.04	0.19
Production	Exponential	5.91 - 6.28	0.37
Production	Power	5.73 - 6.11	0.38
Fully	Exponential	5.91 - 6.30	0.39
Fully	Power	5.90 - 6.30	0.40

As major corridors of movement are more relevant to strategic planning eight radial routes and four circumferential routes were identified for further analysis. Individual link assignments were aggregated for each corridor and an even wider range of parameter values were noted before the ordering of corridors altered. For example, it was possible to change the parameter in the power function from 1.5 (which gave a mean trip length of 5.5 km.) to 1.9 (which gave a mean trip length of 6.5 km.).

This theoretical study was repeated with real data for the English city of Bradford (West Yorkshire). The origin-destination pattern of journey-to-work by motor-car was extracted from the 1966 Census of Population. The twenty-four zones were connected by a main road network with 220 directional links. Road distance was used in the gravity model impedance function and to construct the shortest inter-zonal travel paths.

Gravity models were calibrated against the survey mean trip length of 5.5 km, and the parameter values were then changed systemmatically. The interpretation of the traffic assignments was more difficult because of the size of the network but in general an acceptable degree of consistency was found for the heavily trafficked links for different parameter values. For example, Table 2 gives the number of links ranked incorrectly for the fully constrained exponential model (statistically the best model), given parameter changes that produce mean trip lengths of up to 0.4 km. either side of the correct figure of 5.5 km.

Table 2: Gravity Model Sensitivity Analysis, Bradford

Divergence from Observed Mean Trip Length (km.)	Number of Major Links Ranked Incorrectly
0	0
± 0.1	1
± 0.2	4
± 0.3	6
± 0.4	12

One implication of this research is that for long-term strategic planning there is little need to calibrate models tightly against survey data. More simplified models could well serve the same purpose. Appropriate models for strategic planning purposes are discussed in detail elsewhere (Black, 1980b).

MULTI-OBJECTIVE PROGRAMMING

Single objective optimisation models have limited practical applications in planning because a decision based on one criterion is unlikely to reflect community preferences in a pluralistic society. However, multi-objective programming is a promising tool in decision-making, planning and design (Nijkamp and Rietveld, 1976).

Mathematically, the problem is to find a set of numerical values for variables which can be manipulated by the planner (control variables) in such a way that the multiple objectives and constraints are satisfied.

$$\max F\left(f_1, f_2 \ldots f_n \right)$$

where,

$f_1 = f_1(x)$; x is a vector of decision variables,

such that,

$x \in A$; the decision is made within the feasible region A, as defined by the constraints.

The pay-off table is a matrix of values for the objectives in which each of the goals is optimised independently. The diagonal entry is the optimal value of each objective function ($f_i^* \leq f_i^n$)

objective	1	2	3	....	n
1	f_1^*	f_2^1	f_3^1		f_n^1
2	f_1^2	f_2^*	f_3^2		f_n^2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots\vdots\vdots$	$\vdots$
n	f_1^n	f_2^n	f_3^n	...	f_n^*

The fact that different groups (with different priorities) might be involved in a decision means that an unambiguous ranking of objectives is impossible. Interactive programming is a man-machine system where the analyst confronts a decision-maker with questions about trade-offs between the conflicting objectives (Dyer, 1973). The information is used to arrive at a compromise solution, yet still within the feasible region. Such a process is required when the decision-maker is unaware or unsure of the relative importance (weighting) of each objective.

Consider the following illustrative worked example. The problem is to allocate 9000 workers to three residential zones and 9000 jobs to two employment zones, subject to simple physical constraints concerning the minimum threshold and the maximum permissible zonal development. There are four objectives: minimisation of total development costs; minimisation of total transport costs; minimisation of environmental disruption to people living along the proposed transport routes; minimisation of fuel.

Hypothetical data were assumed for zonal development costs, inter-zonal distances, transport construction costs, fuel consumption and the frontage population. The definition of the variables and the notation is as follows:

R_i = number of workers allocated to residential zone i;

E_j = number of jobs allocated to employment zone j;

x_{ij} = number of work trips from zone i to zone j;

a_i = residential development costs in dollars;

b_j = employment development costs in dollars;

c_{ij} = construction costs in dollars from zone i to zone j;

d_{ij} = distance in kilometres from zone i to zone j;

e_{ij} = fuel consumption in litres from zone i to zone j;

p_{ij} = number of people fronting on to the transport link between zone i and zone j.

The problem is to minimise:

$$f_1 = \sum_i a_i R_i + \sum_j b_j E_j$$

$$f_2 = \sum_i \sum_j c_{ij} \cdot d_{ij} \cdot x_{ij}$$

$$f_3 = \sum_i \sum_j e_{ij} \cdot d_{ij} \cdot x_{ij}$$

$$f_4 = \sum_i \sum_j p_{ij} \cdot x_{ij}$$

such that the following constraints are satisfied:

$$1000 \leq R_1 \leq 7000 \qquad R_1 + R_2 + R_3 = 9000$$
$$3000 \leq R_2 \leq 4000$$
$$2000 \leq R_3 \leq 4000$$
$$2000 \leq E_1 \leq 5000 \qquad E_1 + E_2 = 9000$$
$$4000 \leq E_2 \leq 6000$$
$$\sum_j x_{ij} = R_i$$
$$\sum_i x_{ij} = E_j$$
$$x_{ij} \geq 0$$

The traffic desire-line, x_{ij} is taken as the control variable because it implicitly gives the spatial distribution of population and employment.

MPOS (multi-purpose optimisation system), for use on the Cyber system at the University of New South Wales, was the computer package program which solved the above problem. Each objective function was optimised seperately and results are given in the pay-off matrix (expressed in units of one thousand):

	f_1	f_2	f_3	f_4
f_1	203	13.9	15.7	9.6
f_2	211	11.0	9.0	9.0
f_3	211	11.0	9.0	9.0
f_4	211	15.4	18.8	7.9

A computer program was written in FORTRAN which applied the Frank-Wolfe algorithm to solve interactive multi-objective programming problems. It is a recursive process to reach a satisfactory compromise solution. The decision-maker is confronted with a series of paired comparisons and asked to indicate a preference for one of two choices, or to indicate indifference between the two (the trade-off solution). One objective is chosen as the reference criterion, and conceptually the aim is to find out how much a decision-maker would 'give-up' from this criterion in order to gain a specified increment in another.

Because there is insufficient space to describe the manual simulation of interactive programming we select total development costs as the reference criterion. Minimisation of development costs ($ 203,000) indicates the following land use allocation: $R_1 = 3000$; $R_2 = 4000$; $R_3 = 2000$; $E_1 = 5000$; $E_2 = 4000$. Interactive programming results in a set of trade-offs. Setting the reference criterion to unity, the relative weights of the other objectives are respectively 1.2, 5, and 20. The direction finding problem now becomes a single objective programming problem:

$$\text{minimise } f_1 + 1.2\, f_2 + 5\, f_3 + 20\, f_4 \;; \qquad x \in A$$

The solution indicates the following compromise land use allocation: $R_1 = 2000$; $R_2 = 3000$; $R_3 = 4000$; $E_1 = 5000$; $E_2 = 4000$.

Although this is a highly artificial example it demonstrates how Type III and IV uncertainties may be handled. Initially, the decision-maker is unaware of the relative importance of conflicting objectives but interactive programming becomes a learning experience where objectives can be modified as the analysis proceeds. Equally important for strategic planning is the ease by which objectives can be altered over time as community or political values change. The search for alternative plans is implicit: although there are many possible solution within the feasible region, multi-objective programming results in the best compromise. A serious drawback to the practical application of interactive programming is the difficulty in specifying the appropriate trade-offs, especially when objectives are incommeasurable.

CONCLUSIONS

Five areas where uncertainty occurs in the strategic land use/ transport planning process were identified. They are: uncertainty in information acquisition; uncertainty in modelling techniques; uncertainty in political values; uncertainty in the comprehensiveness of the plans; and uncertainty in the actions of groups external to the planning process.

The results of research aimed at reducing uncertainty in the second, third and fourth areas were presented. Sensitivity analysis of part of an urban travel demand model tentatively suggests that transport plans may be relatively insensitive to the model specification. Interactive multi-objective programming was introduced as a promising method of training decision-makers to cope with multiple and competing objectives. Indeed, the presence of tightening constraints will be a feature of planning in the 1980s.

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